Historic, archived document

Do not assume content reflects current scientific knowledge, policies, or practices.

United States
Department of
Agriculture

Forest Service

**Intermountain
Research Station**

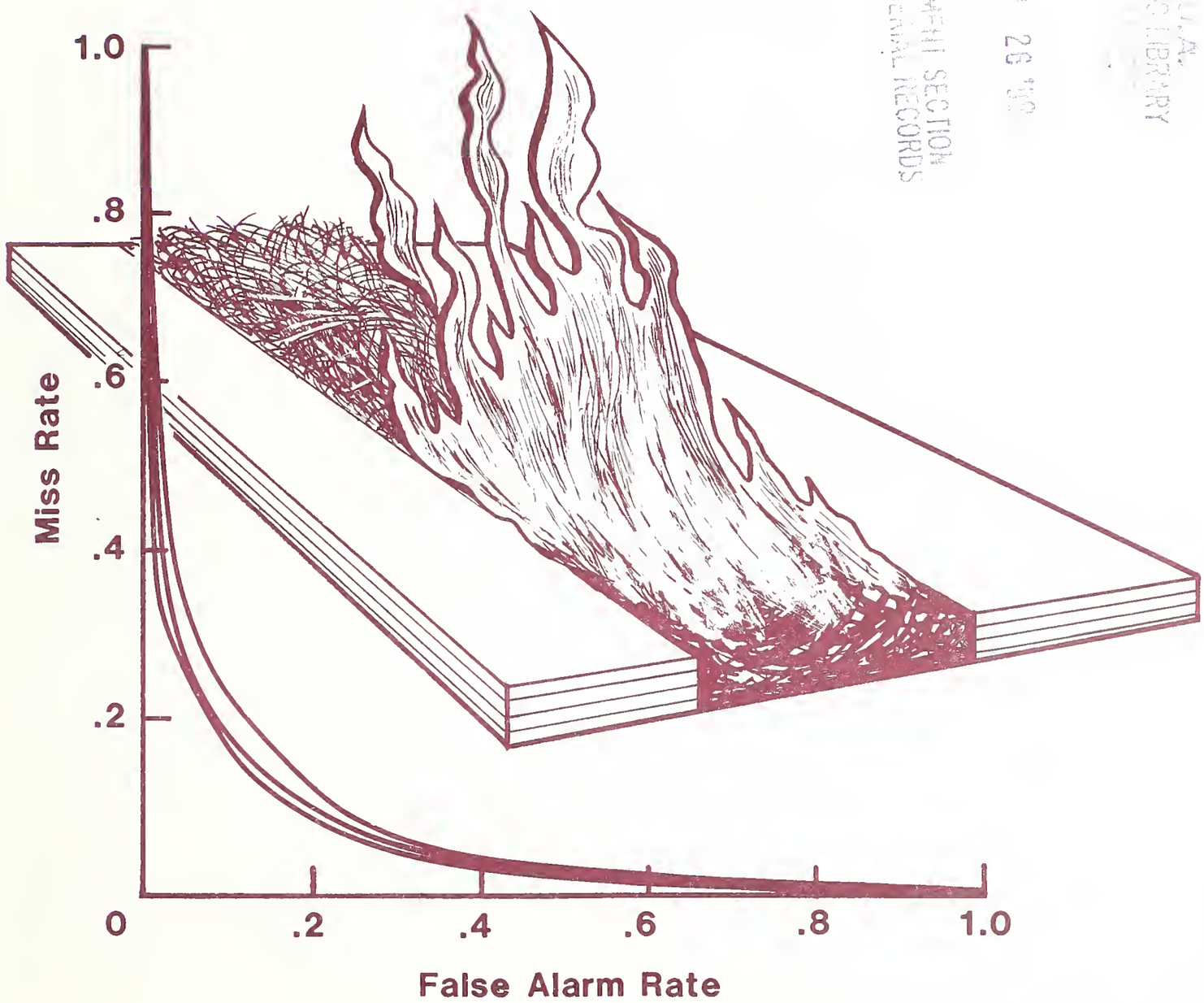
Research Paper
INT-382

A Theoretical Basis for Modeling Probability Distributions of Fire Behavior

Ralph A. Wilson, Jr.

A99.9
F764U
cop. 4

U.S.D.A.
FOREST SERVICE
LIBRARY
JUL 26 '90
PROCUREMENT SECTION
CURRENT SERIAL RECORDS



THE AUTHOR

RALPH A. WILSON is a research physicist assigned to the Fire Behavior research work unit at the Intermountain Fire Sciences Laboratory, Missoula, MT. His undergraduate studies in mathematics and physics were at Willamette University, Salem, OR (B.A. 1956), and his graduate work was in spectroscopy at University of Oregon, Eugene (M.A. 1958). He worked in infrared detectors and optics at the Naval Ordnance Test Station (now Naval Weapons Center), China Lake, CA, from 1957 to 1964. From 1964 to 1975, he worked on the Forest Service's airborne infrared forest fire surveillance project at the Northern Forest Fire Laboratory (now Intermountain Fire Sciences Laboratory).

RESEARCH SUMMARY

A method for predicting a range or distribution of expected fire behavior is developed to help fire managers weigh options. A fire model of marginal burning states produces "likelihood" distributions for the expected fire states. These distributions depend only on the current site observations and are independent of the prior fire state history of the site of application.

Using elementary decision theory, a fire manager first chooses a fire state prescription for the site to be burned. Then, from an appropriate decision goal and the prior distribution of the prescribed state, a threshold value of the likelihood for that fire state is calculated and used to decide whether the site conditions are within the burn prescription, thence whether to burn or not burn.

Two types of error rates are calculated for the marginal burning states: the probability that a fire might burn when predicted to not burn and the probability that it might not burn when predicted to burn. A parametric plot of the two error rates is used as a test of the marginal fire state model and demonstrates the model's utility.

September 1987

Intermountain Research Station
324 25th Street
Ogden, UT 84401

A Theoretical Basis for Modeling Probability Distributions of Fire Behavior

Ralph A. Wilson, Jr.

INTRODUCTION

In recent years great progress has been made in applying fire behavior models in fire management systems nationwide—in several cases, worldwide. Similarly, these fire models have provided fire intelligence for an unanticipated variety of administrative decision and planning functions.

The wide acceptance, and particularly the unique situations to which these models have been applied, has caused problems to arise in two interrelated areas: first, it has been necessary to adjust and "fine-tune" fire behavior systems to properly respond to different geographic locations, and second, the resultant fire behavior information provided is often insufficient, inappropriate, or misleading in some special applications. Both problems would be greatly reduced by developing a definitive method of estimating uncertainties, calculating risks of error, or forecasting a range of possible fire behavior.

This paper documents a theoretical basis for implementing predictive distributions of fire behavior and is intended primarily for the use of specialists who design wildland fire models and systems for applying them. Although Bayesian methods are used, the idea is **not** to specifically recommend a Bayesian Decision System, but rather to show how predictive distributions could be used by the decision makers to specify the inherent limitations of predictive systems, to suggest methods for system optimization for specific applications, and to demonstrate procedures for testing a model's performance. I have tried to "keep it simple" in order to get basic ideas across; thus, I ignore such niceties as distinguishing between continuous and discrete distributions, rigorous use of probability densities, etc., and I avoid complicated derivations.

The central theme of this discussion is that **the fire model** must be universally applicable because fire is a physical process governed by universal physical law; however, a fire model is an **approximation** of real-world fire behavior that implies a degree of uncertainty—uncertainty that must be understood by both the model designer and the manager using the model. Although a model has universal applicability, it is valid **only** within the domain and range of variables for which it is designed, tested, and verified.

In addition, it is emphasized that the prior historical frequency of any predicted fire state is unique to each locality, may be only qualitatively known by local "expert" observers, and is outside the predictive capability of a physical model of fire behavior.

The analysis and solution of these difficulties may be enhanced by using what are sometimes called "Bayesian" techniques—techniques that are quite controversial, yet having some analytical merit. The controversy centers on the admissability of subjective or personal opinion for estimating probabilities as a basis for decision making. Very strong conviction is held on both sides of the controversy: the modern Bayesian theorists emphasize the subjective **personal** decision characterized by the possessive nature of "his goal" and "his objective." In the following development, reference to subjective estimation is made where it may apply. The decision mechanics, risk, and error analysis techniques are reliable and standard engineering practice. These concepts will be illustrated using the following example.

EXAMPLE OF FIRE STATE MODEL AND OBSERVATIONS

In field application, a fire model is combined with **prior** knowledge of the local historical record to arrive at a **posterior** estimate (prediction) of events. The model itself requires **observation**s of specific variables for the current conditions. (The terms "prior" and "posterior," respectively, refer to knowledge before and after the observations; "observer" refers to the manager-decision maker.)

Models are commonly constructed on the basis of **posterior** results of research experiments, but then improperly represented as posterior field predictions. Neglected is the fact that the **prior** conditions of the experiment are different from those in the field application! A properly designed model must express the likelihood that the current situation would be observed if, indeed, the given fire state would occur. When so designed, the fire model is independent of the "prior" conditions of the specific application and the experimental conditions from which it was developed.

It has been demonstrated (Wilson 1985) that the marginal limits of combustion may be represented to an observer as probabilistic distributions of "fire states." The distributions are functions of a parameter, n, which summarizes in a single number all current fuel **observations** and physically resembles a dimensionless burning rate; this parameter is a deterministic function of the physical fuel properties in a manner similar to traditional fire models:

$$n = \frac{\ln(\sigma\beta\delta\, h/Q_w)}{Q_{ig}/Q_w} \qquad (1)$$

where the nomenclature is similar to the original Rothermel (1972) model of fire spread:

- σ = fuel particle surface area to volume ratio
- β = fuel bed packing ratio, solid fuel volume/total bed volume
- δ = fuel bed depth
- h = heat of combustion of the fuel pyrolizate gases
- Q_{ig} = heat for pyrolysis (formerly heat of preignition) of fuel
- Q_w = heat of moisture desiccation (heat scaling factor).

The numerator of equation 1 represents the heat production rate of the fire and the denominator represents the energy needed to heat and pyrolize the fuel.

The burning **state** of a fire is only probabilistically determined even under the most elaborate experimental controls. Figure 1 shows the (posterior) experimental probability distributions for fire states, b_i and $\not{b}_i$. For purposes of this example, these fire states are defined by the fraction of fireline aflame:

- b_1 is the state with fraction of fireline aflame larger than zero
- $\not{b}_1$ is the state of fire that is out; $\not{b}$ is read "not b"
- b_2 is the state with fraction of fireline aflame larger than 0.5
- $\not{b}_2$ is the state with fraction of fireline aflame less than 0.5
- b_3 is the state with fraction of fireline aflame larger than 0.99
- $\not{b}_3$ is the state with fraction of fireline aflame less than 0.99.

In this example, the range of b is bounded with both upper and lower limits: at the lower limit by b_1, fires with zero percent of fireline aflame and at the upper limit by b_3 with 99 percent aflame. By this mechanism we were able to define and observe **marginal** burning.

In the discussion below, a fire state "window" is defined by the conjunction of two elementary states. For example, $b_z = (b_1, \not{b}_2)$ is the state with fraction of fireline greater than zero and less than 0.5. These fire states are defined in terms of an observable fire characteristic that might be related to a "fire effect," treatment, or prescription such as mineral soil exposure, fuel reduction, etc. Promising alternative fire states could be defined by fire intensity, flame length, or by spread rate itself, for example. The fire state as defined above will serve for illustration.

The results of Wilson's (1985) experiment with almost 500 fires, as shown in figure 1, are potentially misleading when applied to field problems. The results correctly show the fire state probability distributions, $P(b|n)$, **for the source experiment**. But that experiment was designed to examine fires near the limit of sustained combustion; thus, 38 percent of the test fires went out, $P(b_1) = 0.62$, 52 percent burned with more than half of the fireline aflame, $P(b_2) = 0.52$, and 32 percent burned with a full contiguous flame front, $P(b_3) = 0.32$. A resource manager

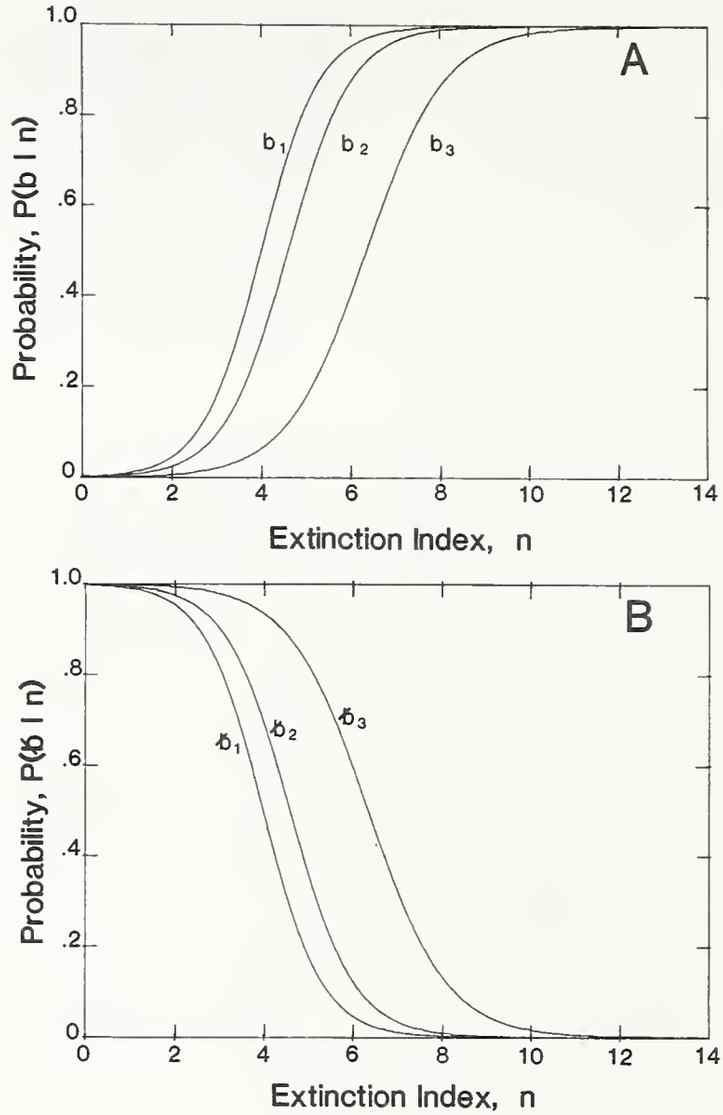


Figure 1—The posterior conditional probability distributions for the three marginal fire states defined in the text (after Wilson 1985).

is going to expect more than 62 percent of the brush fires in southern California in August to be self-sustaining.

The marginal frequency distribution of fire states, $P(b)$, (namely, the "prior" probability of b) in Wilson's experiment is unique to that experiment; that specific distribution is a consequence of the experimental design. Thus, the results plotted in figure 1 are "biased" by the design of the experiment and different results should be expected in other applications that will have different "prior" fire state probability distributions.

In the following discussion, the experimental results (fig. 1) are transformed into "likelihood ratios" (fig. 2) that measure the strength of the observational evidence, n, alone; this measure is independent of the prior probabilities and thus is more universally applicable. The review of decision theory and error analysis follows (Egan 1975). The illustrative example is the work of the author.

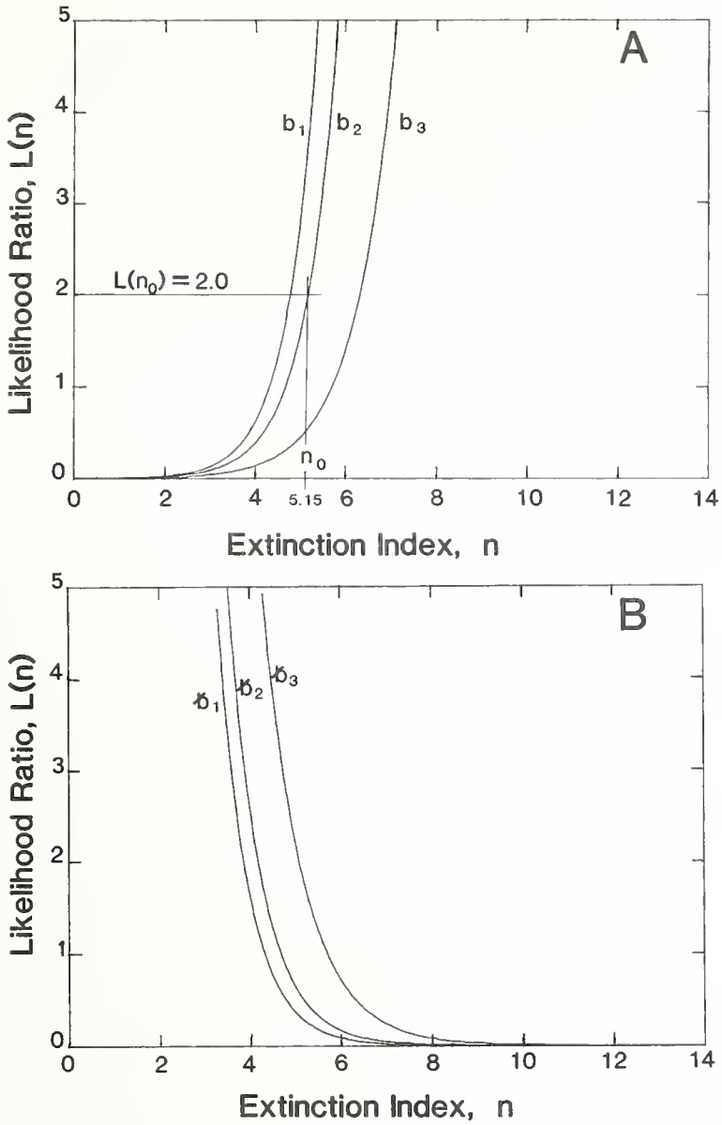


Figure 2—The likelihood ratios for the marginal fire states.

PROBABILITIES, DECISIONS, AND RISK

Let us suppose a fire manager must decide "Do I try this prescribed burn today?" The objective of the burn might be to expose mineral soil and reduce fuels. This treatment requires the **fire state** to burn within specific limits defined by the fire prescription. The manager must decide "yes" (to burn) or "no" (not to burn). In either case, there are two possible events (outcomes or results), depending on fuels and environmental conditions: (1) the fire might burn in a state, b, to accomplish his management goal or (2) it might not burn, $\not{b}$, in that state.

Many decision problems can be reduced (or combined) to just two responses (decision alternatives) and two events (or outcomes). The manager's task is to decide, Y or N, on the basis of uncertain evidence, n, whether his objective will obtain, b, or not obtain, $\not{b}$. For example, there are four possible outcomes: the conjunction (Y,b) is a "correct acceptance" or a "hit" and its complement (N,b) is a "false rejection" or a "miss"; the conjunction $(N,\not{b})$ is a "correct rejection" and its complement $(Y,\not{b})$ is a "false acceptance" or a "false alarm." In decision theory, the two conjunctions (N,b) and $(Y,\not{b})$ are called errors of the first kind and errors of the second kind, respectively; the first is a missed detection (rejecting a true hypothesis), the second is a false alarm (accepting a false hypothesis) (see table 1).

His knowledge being imperfect, the manager's goal is to make a decision with the highest probability of achieving his objective. The manager cannot be criticized for a "bad" result of such rational decision. In the real world of imperfect knowledge, a non-zero probability exists that a good decision may have a bad result and, conversely, a bad decision may have a good result.

The performance of an observer (the fire manager) in a single decision trial is assessed in terms of the probabilities of a correct decision, $P(C)$ and error $P(E)$:

$$P(C) = P(Y,b) + P(N,\not{b})$$

$$P(E) = P(Y,\not{b}) + P(N,b)$$

where, for example, $P(Y,b)$ is called the **joint probability**, that is, the probability that the event, b, and the response, Y, both occur on the same trial.

Objective, Goal, Function, Rule

We now divide the decision process into a logical sequence: first, the manager-observer predetermines an explicit management **objective** and a specific decision **goal**: from the goal a decision **function** is defined, which value depends on the decision of the observer; in turn, a **decision rule** is determined that maximizes (or minimizes) the decision function. For example,

— the objective might be to burn a fire in the state, b,

— the goal might be to have the largest probability of a correct decision,

— then the decision function is $P(C)$ as shown above,

— the decision rule is then, to "say YES" if the posterior probabilities (determined by the observations and prior probabilities) favor maximizing the decision function, $\max P(C)$.

Examples of classical decision goals include:

1. The resource manager may wish to simply maximize the probability of a correct decision, $\max P(C)$, as indicated above.
2. In cases with significant values at risk, the manager may wish to maximize the expected value (or minimize risk).

Table 1—Event-response conjunctions, A, and conditional probabilities, B

A.	Response		B.	Response	
Event	Y	N	Event	Y	N
b	(Y,b) "hit"	(N,b) "miss"	b	$P(Y\|b)$ "hit rate"	$P(N\|b)$ "miss rate"
$\not{b}$	$(Y,\not{b})$ "false alarm"	$(N,\not{b})$ "correct reject"	$\not{b}$	$P(Y\|\not{b})$ "false alarm rate"	$P(N\|\not{b})$ "reject rate"

3. An observer may wish to minimize the maximum probable error rate, the "minimax observer"; this case is of particular interest when the max$P$(C) observer has unknown (or very uncertain) prior probabilities.

4. Other examples of decision goal optimization are contained in the literature; most are variations of these examples. (A fire department might fix a given, tolerable false alarm rate and then work to minimize the rate of missed fire detections; this is the goal of the classical Neyman-Pearson observer, for example.) We will confine our discussion to the above three examples for illustration.

In classical discussion, probabilities are interpreted in a frequency sense; in an indefinite number of observations, an event could be expected to occur in some explicit fraction of the repetitions. But probability is commonly used in another, subjective sense (Larson 1969); for example, "The probability is 10 percent that it will rain tomorrow," or "The chances are 8 to 2 that the fire intensity will be between 3,000 and 5,000 Btu/s·ft^2." These latter examples of subjective probabilities measure an individual's "degree of belief" in a proposition (Savage 1954). That expert opinion (the result of experience) should be expressed in terms of subjective (or personal) probabilities is an implicit tenet of the Bayesian approach to decision theory (Slovic and Lichenstein 1971).

The so-called prior probabilities, $P(b)$ and $P(\not b)$, concern the relative frequency of occurrence of the respective events and are usually estimated from historical data. The prior historical occurrence of any distribution of fire states must certainly vary from locality to locality and the effect is neglected in current application. Data sources (other than personal experience) might include documented fire histories and climatologic records, for example. Some authors emphasize the admissibility of uncertainty and "subjective degrees of belief" in the prior probabilities and advise the choice of prior probabilities with large variance if one is less certain. One should always use the best information available. In a specific decision context, prior probability data is assumed to be fixed (constant and unalterable for that decision) and the occurrence, b or $\not b$, on any given trial is independent of what may have happened on any previous trial.

In addition to prior knowledge, the rational manager also makes observations of the current situation and incorporates this (imperfect) knowledge into his decision. The observer first estimates the likelihood for good or bad outcome based on skillful evaluation of the observations, n, alone. The observations, n, (in future models) might include an exhaustive list of all known physical variables affecting fire behavior such as fuels, topography, and weather; of course, any prediction, Y or N, will still have some chance of being incorrect. In this process, the rational decision maker uses a **fire model**, either systematically, as in equation 1, or intuitively, to calculate the likelihood rates at which the observations alone favor each of the four event/response conjunctions (table 1). Then the decision is made by comparing the possible outcomes with the prior odds of the current application (if they are known).

The "hit" rate, $P(\mathrm{Y}|b)$, is the conditional probability of a response "yes" given the event, b, would occur; and similarly for the other conditional probabilities (table 1). Note that $P(\mathrm{Y},b)$ is the probability of a "hit" and $P(\mathrm{Y}|b)$ is the "hit rate." The joint probabilities of each possible outcome are as follows:

$P(\mathrm{Y},b) = P(\mathrm{Y}|b)\,P(b)$ correct acceptance, "hit"

$P(\mathrm{N},b) = P(\mathrm{N}|b)\,P(b)$ incorrect rejection, "miss"

$P(\mathrm{N},\not b) = P(\mathrm{N}|\not b)\,P(\not b)$ correct rejection, "reject"

$P(\mathrm{Y},\not b) = P(\mathrm{Y}|\not b)\,P(\not b)$ incorrect acceptance, "false alarm."

and

$$P(\mathrm{C}) = P(\mathrm{Y}|b)P(b) + P(\mathrm{N}|\not b)P(\not b) \tag{2}$$

$$P(\mathrm{E}) = P(\mathrm{N}|b)P(b) + P(\mathrm{Y}|\not b)P(\not b). \tag{3}$$

It also follows that:

$$P(\mathrm{Y},b) + P(\mathrm{N},b) + P(\mathrm{Y},\not b) + P(\mathrm{N},\not b) = 1.0 \tag{4}$$

$$P(b) + P(\not b) = 1.0 \tag{5}$$

$$P(\mathrm{Y}|b) + P(\mathrm{N}|b) = 1.0 \tag{6}$$

$$P(\mathrm{Y}|\not b) + P(\mathrm{N}|\not b) = 1.0. \tag{7}$$

The foregoing equations are a result of how the decision situation is set up and the algebra of probabilities. For example, equation 5 says (or implies) that the fire will accomplish the objective, b, or it will not; there is no middle ground or alternative. Equations 6 and 7 say that I must make a decision; for example, if I refuse to make a decision (after I have accepted the objective), then one of either Y or N must occur by default. Equation 4 says that one of the results (event/responses) of table 1 must occur, and taken with equations 2 and 3, my decision will be right or wrong!

In the interest of generality, we note that most decision problems can be reduced to the two-event, two-response situation. To illustrate, a certain fire treatment may require a residence time, b_1, flame lengths not to exceed, b_2, etc.,. . . b_k; this series of specifications may be summarized in a single prescription, $\mathbf{b}_x$, which is the simple conjunction of the individual requirements:

$$\mathbf{b}_x = (b_1,\ b_2,\ \ldots,\ b_k)$$

Similarly, observational data on fuels, n_f, meteorology, n_m, and topography, n_t, will be represented by the conjunction:

$$\mathbf{n}_x = (n_f, n_m, n_t,\ \ldots)$$

and furthermore, the joint probability that $\mathbf{b}_x$ and $\mathbf{n}_x$ occur is given by

$$P(\mathbf{b}_x,\mathbf{n}_x) = P(b_1,b_2,b_3,\ldots,b_k|n_f,n_m,n_t,\ldots)\,P(n_f,n_m,n_t,\ldots)$$
$$= P(\mathbf{b}_x|\mathbf{n}_x)P(\mathbf{n}_x).$$

The premise of the formal decision procedure is that the vector, $\mathbf{b}_x$, contains sufficient and necessary information to best define the management objective and that the vector, $\mathbf{n}_x$, be a proper decision discriminator.

The so-called posterior conditional probability, $P(\mathbf{b}_x|\mathbf{n}_x)$ (hereafter written $P(b|n)$) is **the single most important probability** for the decision maker. Many "old firehorses" are respected because of their skill at estimating prior probability (from previous experience) combined with estimating (most often by subjective intuition) the probability that a result will occur, given the current observations, and also for the courage to act despite risk. The following development describes a procedure to systematically optimize this decision process.

The Bayesian model (variously called Bayes rule, theorem or function, after the Reverend Thomas Bayes, ca. 1763) states that

$$P(b_i|n) = \frac{P(n|b_i)P(b_i)}{\sum_j (P(n|b_j)P(b_j))} = \frac{P(n|b_i)P(b_i)}{P(n)} \quad (8)$$

provided that the b_j are mutually exclusive and exhaustive. $P(b_i|n)$ is the posterior probability that b_i is true, taking into account the new data, n, and the prior probability, $P(b_i)$; that is, $P(b_i|n)$ is a function of b_i with the "given" parameter set to n. $P(n|b_i)$ is the conditional probability that n would be observed when we assume b_i is known; that is, $P(n|b_i)$ is a function of n with the "given" parameter set to b_i. (Because n is a continuous function of the fuel bed parameters, these probabilities are known rigorously as probability densities. This distinction is not germane to this discussion, so we will maintain the notation, P, etc., for simplicity. Bayes theorem is succinctly discussed by Hahn and Shapiro [1967].) This latter distribution, $P(n|b_i)$, thus models the current physical conditions independent of the prior occurrence of b_i, and should be more universally applicable. $P(n|b_i)$ is determined from previous observational experience or from independent experimental research as demonstrated in the example. It is sufficient here to note the following identities:

$$P(n,b) + P(n,\not{b}) = P(n) \quad (9)$$

$$P(b|n) + P(\not{b}|n) = 1.0 \quad (10)$$

or

$$P(\not{b}|n) = 1 - P(b|n), \text{ etc.} \quad (11)$$

It is convenient to form the ratio of equation 8 with respect to the two states b and $\not{b}$ (in order that the dependence on the frequency distribution of observations, $P(n)$, be removed); b and $\not{b}$ are two arbitrary, mutually exclusive and exhaustive fire states, namely, those that will burn within some fire prescription and those that will not, respectively. Then

$$\frac{P(b|n)}{P(\not{b}|n)} = \frac{P(n|b)}{P(n|\not{b})} \times \frac{P(b)}{P(\not{b})}. \quad (12)$$

The left-hand side of equation 12 is the ratio of posterior probabilities (conditional on the observations, n) and gives the odds that the fire will burn in the state b. Henceforth, "odds" will specifically mean a ratio of probabilities whereby odds may assume values greater than 1.

The right-hand side of equation 12 shows explicitly that two types of information enter into the calculation of the posterior odds. The second term on the right, the ratio of prior probabilities, summarizes the observer's imperfect knowledge about the relative frequency of occurrence (odds of b vs. $\not{b}$) before the evidence, n, was observed, as before.

The first ratio on the right of equation 12 is

$$L(n) = \frac{P(n|b)}{P(n|\not{b})}. \quad (13)$$

$L(n)$ is called the **likelihood ratio** and gives the likelihood (odds) of observing the evidence, n, on a b trial relative to observing the same evidence on a $\not{b}$ trial; $L(n)$ contains exclusively the information provided by the universal fire model. It is implicit that the evidence, n, is "good" data and that it is appropriate to the decision process to the degree that it makes the likelihood ratio a good decision discriminator. In the example (fig. 2A), Wilson's experimental results are transformed to remove the dependence on his prior experimental design and are presented as likelihood ratios; the likelihood ratios for the $\not{b}$ states shown in figure 2B are the respective inverses of the b state ratios as a consequence of equation 13. The functions $L(n)$ for the individual fire states are shown to be monotonic continuous functions of the parameter, n, and thus suitable discriminators for decision criteria. Note again that the prior odds of achieving a certain fire state (or fire prescription) will change from place to place (and time to time), but lack the benefit of specific information, n, while the likelihood ratio responds only to the current physical conditions, n, in the same manner for any given place or time.

The Max$P$(C) Observer

The objective is to burn a fire in the state b. The goal of the max$P$(C) observer is to have the maximum probability of a correct decision; cost and reward values are not involved. But the probability estimate of a correct decision depends on the current observations of the physical fire environment **and** the prior frequency distribution of the fire states in the given local situation.

As already shown, most basic decisions may be reduced to just two events, b and $\not{b}$, and two responses, Y and N, with the resulting four event-response conjunctions. On each trial, the observer's decision is based on the specific evidence, n. We assume that the observer has calculated (subjectively or otherwise) the prior probabilities and the likelihood ratio of the evidence, n. Thus, the maximum P(C) observer knows the posterior odds, $P(b|n)/P(\not{b}|n)$, of the event, b, etc.

With reference to table 1, clearly the "correct" conjunctions (Y,b) and (N,$\not{b}$) are preferred by the maximum P(C) observer, that is, we wish to maximize the decision function (equation 2):

$$P(\text{C}) = P(\text{Y}|b)P(b) + P(\text{N}|\not{b})P(\not{b}).$$

Following the development above, this observer's decision rule is to say "yes" if the posterior odds favor the event b; otherwise, say "no." Thus, he should say "yes" if

$$\frac{P(b|n)}{P(\not{b}|n)} > 1$$

or by rearrangement, using equations 12 and 13, we have the **Max$P$(C) decision rule**:

$$\text{if } L(n) > \frac{P(\not{b})}{P(b)}, \text{ say "yes," otherwise say "no."}$$

No larger P(C) can be realized by an observer who adopts any other decision rule. This criterion also minimizes the error probability of equation 3.

Suppose a manager wishes to burn a fire in the state b_2 and in the present local situation (known to be poor burning conditions by prior experience), the prior odds suggest that b_2 is unlikely, say $P(b_2) = 1/3$, inferring a threshold value of $L(n)$:

$$L(n_0) = \frac{P(\not{b}_2)}{P(b_2)} = \frac{2/3}{1/3} = 2.0$$

as shown in figure 2A. Then, if the observation, n (based on fuel moisture or fuel loading) exceeds $n_0 = 5.15$, he proceeds with the prescribed burn. Note that if $P(b_2)$ is more likely, the threshold, $L(n_0)$ is smaller and he may try the burn at lower n, that is, higher fuel moisture or lighter fuel load; and conversely, for more unlikely $P(b_2)$. Thus, a rational format is suggested whereby a universally applicable fire model is appropriately adaptable to any local situation!

The Expected Value Observer

The manager faced with a decision involving major values at risk (the risk of large costs or potentially large benefits) will have at hand all relevant information to estimate a payoff matrix associated with the net value of each conjunction as shown in table 2. This observer also has information to estimate the posterior odds, etc. We construct two decision functions dependent on the evidence, n, and the respective responses, "yes" and "no":

1. The expected value, $E(V|n,\mathrm{Y})$, if the observer says "yes," and
2. The expected value, $E(V|n,\mathrm{N})$, if the observer says "no."

The two values of the payoff matrix associated with the "yes" response are weighted by the appropriate posterior probability rate

$$E(V|n,\mathrm{Y}) = P(b|n)V_{\mathrm{Y},b} + P(\not{b}|n)V_{\mathrm{Y},\not{b}}. \tag{14}$$

Similarly, for the response "no"

$$E(V|n,\mathrm{N}) = P(b|n)V_{\mathrm{N},b} + P(\not{b}|n)V_{\mathrm{N},\not{b}}. \tag{15}$$

Then, clearly, the observer should say "yes" if the expected value of the "yes" response is greater than the expected value of the "no" response, that is,

if $E(V|n,\mathrm{Y}) > E(V|n,\mathrm{N})$ say "yes," otherwise say "no."

From equations 14 and 15, this rule is expressed in terms of the posterior odds:

$$\text{If } \frac{P(b|n)}{P(\not{b}|n)} > \frac{V_{\mathrm{N},\not{b}} - V_{\mathrm{Y},\not{b}}}{V_{\mathrm{Y},b} - V_{\mathrm{N},b}},$$

say "yes," otherwise say "no,"

or in terms of the likelihood ratio and prior odds, **the expected value decision rule** becomes

$$\text{If } L(n) > L(n_0) = \frac{P(\not{b})}{P(b)} \cdot \frac{V_{\mathrm{N},\not{b}} - V_{\mathrm{Y},\not{b}}}{V_{\mathrm{Y},b} - V_{\mathrm{N},b}}, \tag{16}$$

say "yes," otherwise say "no."

Note that if the payoff matrix has equal values for the respective b and $\not{b}$ events, then the maximum expected value observer obtains the same result as the max$P$(C) observer. The second ratio on the right-hand side of equation 16 contains exclusively the values and costs involved in the decision. The numerator expresses the "yes-no" value difference (the value of being correct minus the value of error), if $\not{b}$ prevails; the denominator similarly if b prevails. The value ratio is an expression of the relative importance of the two events, $\not{b}$ and b. In many cases,

Table 2—Payoff matrix of values for event/response conjunctions

	Response	
Event	Y	N
b	$V_{\mathrm{Y},b}$ value of success	$V_{\mathrm{N},b}$ cost, missed opportunity
$\not{b}$	$V_{\mathrm{Y},\not{b}}$ cost of failure	$V_{\mathrm{N},\not{b}}$ savings for not trying

where explicit values are lacking, the manager assigns a numerical factor that expresses his rational judgment of the relative importance of the two events. Many rational decisions are made to proceed with a task, often against large odds, simply because the manager needs (values?) to get the job done. An example for a specific prescription window is illustrated below.

Decisions Without Prior Odds and ROC Curves

The observer may use a threshold value of the likelihood ratio as the basis of his decision, even though the prior odds are unknown, thus basing the decision on the observations alone (this is the same as assuming, for example, that $P(b) = P(\not{b})$). (The detractors of the modern Bayesian theorists argue rhetorically that if the "prior" probability distributions are unknown, then this assumption is equivalent to "the equal distribution of ignorance.") Or, as in figure 2A, he may simply want the likelihood ratio of the observations to favor b over $\not{b}$ by 2:1 odds, etc. A given threshold, $L(n_0)$, implies a specific cutoff value, n_0, as the equivalent basis of the decision, namely, a decision rule (defined below) may require "say yes" if $n > n_0$, otherwise "say no." Furthermore, the probability distributions, $P(n|b)$ and $P(n|\not{b})$, are assumed to be known as in the illustrative example. Then we can define the "miss rate" and "false alarm rate," respectively, as:

the miss rate,

$$P(\mathrm{N}|b) = P(n < n_0|b)$$

$$= \int_{-\infty}^{n_0} P(n|b)\,\mathrm{d}n = \int_{-\infty}^{n_0} \frac{P(b|n)P(n)}{P(b)}\,\mathrm{d}n \tag{17}$$

$$= 1 - \int_{n_0}^{\infty} P(n|b)\,\mathrm{d}n, \tag{17A}$$

and false alarms,

$$P(\mathrm{Y}|\not{b}) = P(n > n_0|\not{b})$$

$$= \int_{n_0}^{\infty} P(n|\not{b})\,\mathrm{d}n = \int_{n_0}^{\infty} \frac{P(\not{b}|n)P(n)}{P(\not{b})}\,\mathrm{d}n. \tag{18}$$

Thus, the mechanics for calculating the error rates associated with the observational model are specified. Note also

that the other two conditional probabilities for the truth (table 1B) are determined by use of equations 6 and 7. Then the two error rates are plotted parametrically over the domain of $n_0(-\infty < n_0 < \infty)$ as in figure 3B. (Such plots are called receiver operating characteristic (ROC) curves and were first developed by electronic engineers working on search and detection systems during the 1940's and 1950's, thus accounting for much of the terminology: "false alarm," "missed detection," etc.) The "miss" error conditional probability, $P(\mathrm{N}|b)$ is plotted on the ordinate and the "false alarm," $P(\mathrm{Y}|\not{b})$, is plotted as the abscissa. The operating curve thus generated is characteristic of the observation system, namely, it is dependent only on the distribution, $P(n|b)$; note that these error rates are independent of the prior probabilities because we assumed a decision rule based only on a critical value of the observations, n_0.

It is instructive to evaluate the derivative of the miss rate with respect to the false alarm rate at the cutoff, n_0; from equations 17A and 18, we have:

$$\left.\frac{\mathrm{d}\,P(\mathrm{N}|b)}{\mathrm{d}\,P(\mathrm{Y}|\not{b})}\right|_{n_0} = \frac{-P(n_0|b)}{P(n_0|\not{b})} = -L(n_0). \tag{19}$$

Thus, the slope at a point on the error operating curve is equal to the negative of the likelihood ratio, $L(n)$, for the n value associated with that point, recognizing that n_0 is simply a parameter of the foregoing construction. Any decision maker who chooses an operating point on the system's ROC curve is called a "Likelihood Ratio Observer" irrespective of which decision goal he uses to fix the operating point, $L(n_0)$, on the ROC curve.

Let us consider, momentarily, the observer whose goal is simply that the hit rate should equal the false alarm rate, that is, he wants to pick a Y-N cutoff, n_0, such that when he says "yes" he has a successful burn, b, at least as often as he says "yes" and fails, $\not{b}$. The limiting worst case,

$$P(\mathrm{Y}|b) = P(\mathrm{Y}|\not{b}),$$

is shown in figure 3A as the straight line diagonal between the points (0,1) and (1,0). This observer is primarily concerned with the results when his answer is "yes," so consider the sum of joint probabilities:

$$\begin{aligned} P(\mathrm{Y}) &= P(\mathrm{Y},b) + P(\mathrm{Y},\not{b}) \\ &= P(\mathrm{Y}|b)P(b) + P(\mathrm{Y}|\not{b})P(\not{b}). \end{aligned}$$

Impose the limiting condition, $P(\mathrm{Y}|b) = P(\mathrm{Y}|\not{b})$, then because $P(b) + P(\not{b}) = 1$, it follows that

$$P(\mathrm{Y}) = P(\mathrm{Y}|b) = P(\mathrm{Y}|\not{b}) \tag{20}$$

which means that this observer's objective is achieved whenever the probability of a "yes" response is the same when either condition b or $\not{b}$ occurs, that is, he leaves the choice to chance and achieves his objective. The negative diagonal in figure 3A, (0,1) to (1,0), is called the "chance line." The probability of error for this observer is

$$\begin{aligned} P(\mathrm{E}) &= P(\mathrm{N},b) + P(\mathrm{Y},\not{b}) \\ &= P(\mathrm{N}|b)P(b) + P(\mathrm{Y}|\not{b})P(\not{b}) \text{ as before.} \end{aligned}$$

Applying equation 20 and the usual identities and rearranging terms, we have

$$P(\mathrm{E}) = P(b)(1 - 2P(\mathrm{Y})) + P(\mathrm{Y}) \tag{21}$$

from which we see that:

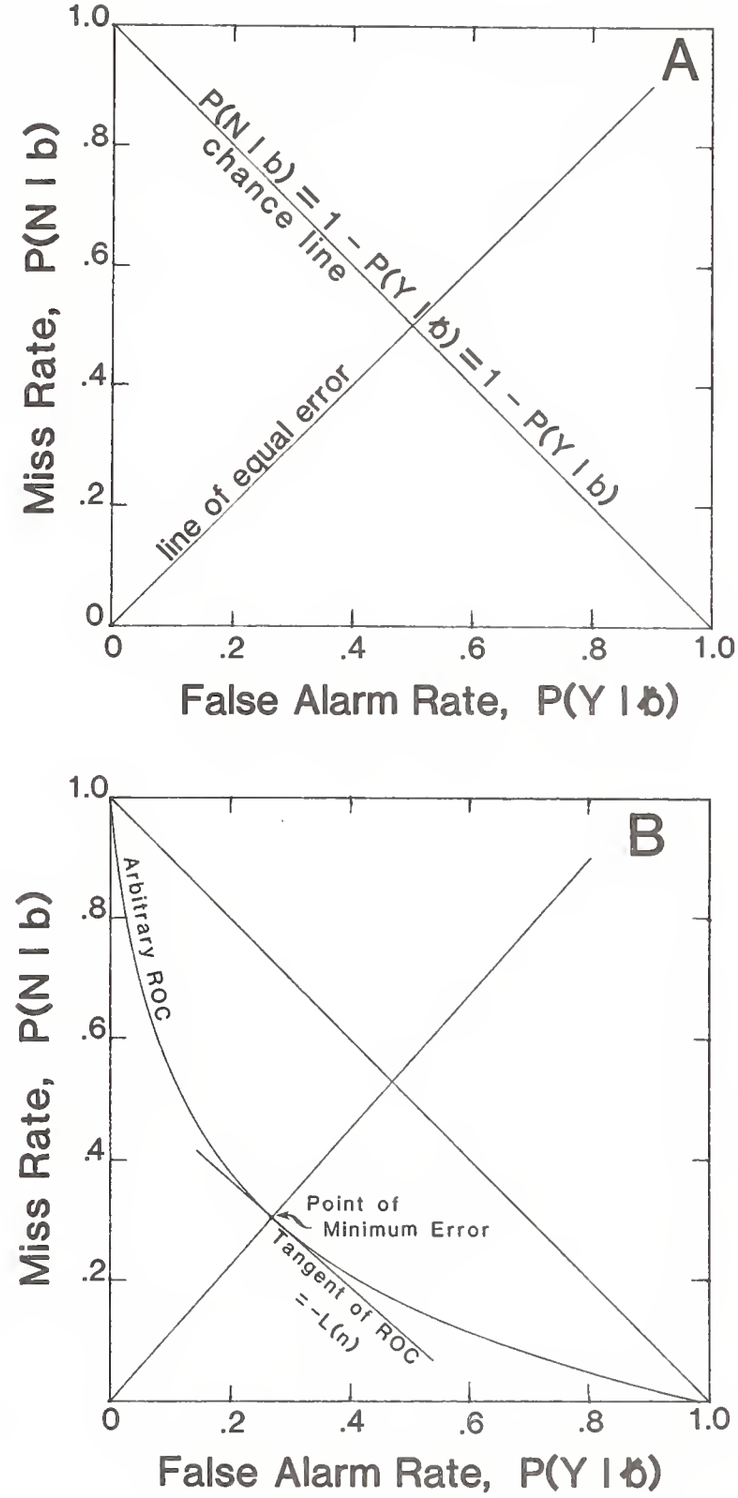


Figure 3—Receiver operating characteristic (ROC) example plot.

1. If the state b is certain, $P(b) = 1$, then the probability of error, $P(\mathrm{E}) = (1 - P(\mathrm{Y})) = P(\mathrm{N})$.
2. Alternately, if $\not{b}$ is certain, $P(b) = 0$, then $P(\mathrm{E}) = P(\mathrm{Y})$.
3. Most importantly, if $P(\mathrm{Y}) = 0.5$ (if the response "yes" is determined by the flip of a fair coin, $P(\mathrm{Y}) = P(\mathrm{N}) = 0.5$), then this observer's error rate is independent of the prior probabilities, $P(b)$ or $P(\not{b})$ as in equation 21;

furthermore, all entries in the 2×2 matrix (table 1B) of conditional probabilities are equal,

$$P(\mathrm{Y}|b) = P(\mathrm{Y}|\not{b}) = P(\mathrm{N}|b) = P(\mathrm{N}|\not{b}) = 0.5, \text{ and}$$

the observer is operating at the (0.5,0.5) point on the ROC chance line. At this point, (0.5,0.5) in figure 3A, the operating curve perpendicularly intersects the line of equal errors and the maximum probable error is a minimum; note that this is the point on the chance operating curve that lies closest to the ROC origin, the origin being the point of zero error. Furthermore, if the observer biases his coin so that the probabilities of "yes" and "no" are unequal, then the operating point (the 2×2 matrix of conditional probabilities) moves away from (0.5,0.5) along the chance line resulting in an increase in the maximum probable error rate.

A decision system's performance is judged by the location of its operating curve. Good performance is measured in the space below the chance line by how close the operating curve approaches the origin, indicating low error rates. It is possible for a decision system to operate in the space above the chance line by using bad decision rules or bad observational data. "Bad information is worse than no information." The manager-observer should learn to recognize such cases, where he is better off flipping a fair coin than using bad information.

The Minimax Observer

Recalling that "good" operating curves occupy the space below the chance line, and are thus convex downward, where either error rate should be monotonically decreasing as the other increases as in the example (figure 3B), we can suggest a decision rule that **minimizes the maximum probable error rate**, independent of any knowledge of prior probabilities. By geometric inspection of figure 3B, one may determine the point of closest approach of an operating curve (analytic or otherwise) to the origin. The shortest line segment from the origin to a point on the operating curve is perpendicular to the tangent, $-L(n_0)$, at that point. Even for imperfect and empirically derived operating curves that point will be more or less close to the intersection with the line of equal error rates.

Our goal, again, is to minimize the probability of error. Setting the derivative of $P(\mathrm{E})$ with respect to the false alarm rate, $P(\mathrm{Y}|\not{b})$, equal to zero gives a minimum and not a maximum because $-L(n)$ is an increasing function of the abscissa, $P(\mathrm{Y}|\not{b})$ (equation 3):

$$P(\mathrm{E}) = P(\mathrm{Y}|\not{b})P(\not{b}) + P(\mathrm{N}|b)P(b)$$

$$\frac{\mathrm{d}\,P(\mathrm{E})}{\mathrm{d}\,P(\mathrm{Y}|\not{b})} = 0$$

$$= P(\not{b}) + \frac{\mathrm{d}\,P(\mathrm{N}|\,b)}{\mathrm{d}\,P(\mathrm{Y}|\not{b})}\,P(b)$$

then again, by equation 19, we have

$$\frac{\mathrm{d}\,P(\mathrm{N}|\,b)}{\mathrm{d}\,P(\mathrm{Y}|\not{b})} = -L(n_0) = -\frac{P(\not{b})}{P(b)}.$$

Thus, $L(n_0) = P(\not{b})/P(b)$, as before, but here we have demonstrated that the point (false alarm rate, miss rate) at which the slope of the operating curve is $-L(n_0)$, is the operating point where the maximum probable error is a minimum; that is, the maximum probable error over all n but a minimum over all possible $P(\mathrm{Y}|\not{b})$ and similarly for $P(\mathrm{N}|b)$.

The ROC is a known characteristic of the observation/prediction model. To operate with minimum error rate, the observer should use **the minimax decision rule**: if $L(n) > L(n_0)$, say "yes," otherwise say "no," where $L(n)$ is the result of observation as before and where $-L(n_0)$ is equal to the slope of the ROC curve at the point of closest approach to the origin; for the minimax observer $L(n_0)$ tends to be more or less close to the line of equal errors (where $L(n_0) = 1$), depending on the precise shape of the ROC at the point of minimum error (note that this observer's goal is to minimize the **error rate** and not the total error as the max$P(\mathrm{C})$ observer above).

An irrational observer could include in his decision rule a few values of n for which corresponding values of $L(n)$ are less than some of those not included in his rule; so, he responds Y to those observations of n that represent less evidence for b than for other good observations to which he responds N. Such an observer is not a likelihood ratio observer! Inescapably, he is still working within the ROC plot, somewhere in the space above the system's ROC curve. It must be emphasized that, for any given false alarm rate, the miss rate cannot be made smaller than that for the **likelihood ratio observer.** (Similarly, for any given miss rate, the false alarm rate cannot be smaller.) Note, however, that the error rates may all vary with the decision rule at the option of the observer.

A city fire department chooses a very low fire detection threshold to reduce errors of the first kind (missed detections) and hence must tolerate many false alarms; alternatively, a forester may pass up several missed opportunities because he cannot risk a bad burn. In both instances, the managers are not acting as minimax observers to minimize total error, but must consider the values and prior probabilities as in the previous examples above. Both are considered good likelihood ratio observers if they choose an operating point ($L(n)$) on their ROC curve.

Prescription Windows

While developing error equations 17 and 18, we assumed a Y/N cutoff in terms of n_0 (not $L(n_0)$) because the arithmetic was easier; $L(n)$ is an equivalent discriminator because it is always a piecewise monotone function of n. $L(n)$ is the more practical in many applications; for example, the likelihood ratio for $b_z = (b_1, \not{b}_2)$ in the example is calculated, following equation 13:

$$L(n) = \frac{P(n|\,b_z)}{P(n|\not{b}_z)},$$

as shown in figure 4A. The decision threshold in b_z is specified by a single value of the odds, $L(n_0)$, whereas to accomplish the same purpose, two very complicated critical values of n would be required: a cuton value, $n_{0,1}$ **near** the b_1 limit, and cutoff value, $n_{0,2}$ **near** the $\not{b}_2$ limit.

In figure 4B, the likelihood ratios are plotted also for the burning windows $(b_1, \not{b}_3)$ and $(b_2, \not{b}_3)$, respectively, the fractions of fireline aflame between 0.01 to 0.99 and between 0.5 to 0.99. Note that the manager might improve

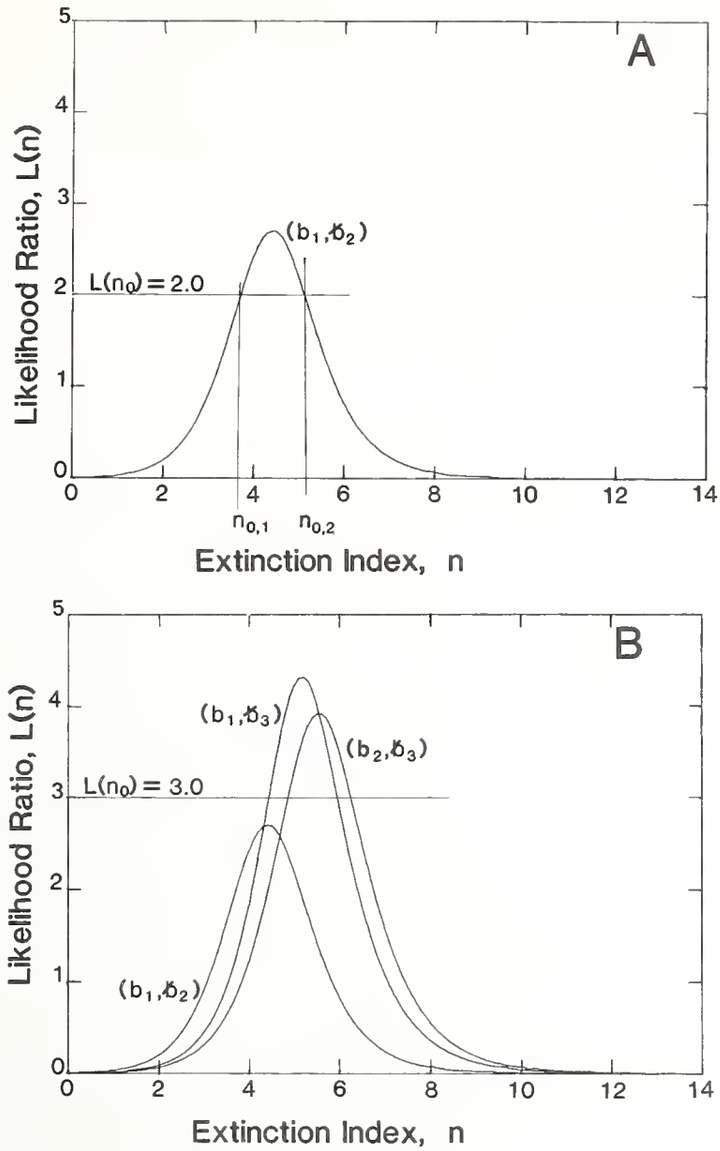


Figure 4—Likelihood ratios for conjunctions of fire states (prescription windows).

the likelihood (odds) of hitting his burning window (by observing a value of n) if the window is wider as in the former case, or the window is moved to better burning conditions as in the latter case. Similarly, if he knows that his prior odds are, say, 3:1 against the prescription $(b_1,\not{b}_2)$, that is, $L(n_0) = 3$, then he cannot rationally expect to hit that prescription; whereas, by widening the window (as in $b_1,\not{b}_3$) two effects improve his chances: first, $L(n)$ will improve as in figure 4B, and secondly, the prior odds against $(b_1,\not{b}_3)$ are expected to be smaller, that is, $L(n_0) < 3$, because, again the historical record will show more fires in $(b_1,\not{b}_3)$ than in $(b_1,\not{b}_2)$.

Suppose, now, a manager has an economically important fire treatment to perform; the fire prescription is $(b_1,\not{b}_2)$ as above with the same prior odds, $P(\not{b})/P(b) = 3$. As an expected value observer, the manager has considered all of the relevant treatment costs and benefits to construct a payoff matrix with the following components:

- If the burn is successful, the net present value would be $V_{Y,b}$ = \$30 per acre. In this simple example, net value is composed of a depreciated future benefit of \$50/acre, less \$10/acre fixed planning and preparation costs and \$10/acre for labor and supplies.
- The missed opportunity value, $V_{N,b}$ = −\$15/acre, includes the \$10/acre fixed cost and \$5/acre associated with the lost opportunity and delayed burning schedule.
- The cost to try and fail, $V_{Y,\not{b}}$ = −\$25/acre, is composed of \$10/acre fixed cost, \$10/acre labor and supply, and \$5/acre loss to present net value due to site damage.
- And, the value of correctly deciding not to burn, $V_{N,\not{b}}$ = −\$10/acre, is just the planning fixed cost.

Then the decision threshold, $L(n_0)$, becomes (by equation 16),

$$L(n_0) = \frac{P(\not{b})}{P(b)} \cdot \frac{V_{N,\not{b}} - V_{Y,\not{b}}}{V_{Y,b} - V_{N,b}}$$

$$= 3 \cdot \frac{(-10) - (-25)}{(30) - (-15)} = 3 \cdot \frac{1}{3} = 1.0.$$

Thus, the effect is to lower the decision threshold, $L(n_0)$, which is readily justified by the expected payoff. Note that the "fixed planning cost" has no resultant effect on the decision function, basically because that cost was incurred (by some previous decision) before we arrived at this decision point and is an obligation regardless of the decision. Also note that generally (not always), the two errors will have less value than their respective correct conjunctions, thus both numerator and denominator of the value ratio (eq. 16) will have positive values. (An exercise for the reader is to consider the dilemma of the manager who "must decide between the lesser of two evils.") In many practical examples, $V_{Y,b}$ will be the dominant positive value; hence the value ratio will have a positive value, less than 1, so the payoff justifies a decision that might otherwise be against the prior odds.

Of course the cost and benefit values in the value ratio are associated with the specific prescription, $b = (b_1,\not{b}_2)$, for example. The manager may consider the tradeoffs of adjusting the prescription window and the corresponding value ratios to arrive at the best possible decision.

If we vary the decision rule to successively enlarge the range of acceptable n, we will start with a large $L(n_0)$ (fig. 4) at the ROC point (0,1) where the acceptable range is zero and (by **any** rational decision rule) we will always say "no" where we will never have a false alarm, where the miss **rate** equals 1.0, and the (joint) probability of a missed opportunity is equal to the (prior) probability of the opportunity. And we will end with a small $L(n_0)$ at the ROC point (1,0) where we always say "yes," never miss an opportunity, but the false alarm rate equals 1.0 and the (joint) probability of a false alarm is equal to the (prior) probability that the opportunity does not occur (refer to equations 2 to 7). Furthermore, the range of acceptable n must be nondecreasing over the entire path because the ROC slope, $-L(n)$, varies so.

Model Performance

An ROC curve is uniquely determined for each pair of distributions, $P(n|b)$, $P(n|\not{b})$, and is the same for all decision rule criteria. There exists, then, a family of ROC curves that depend on the parameter, b; which family is represented by the fire states, b_1, b_2, b_3.

The ROC plot for Wilson's model is shown in figure 5A. The continuous curves are generated by equations 17 and 18, and the respective curves in figure 1. The data points are the appropriate experimental counts of burns, b, and not-burns, $\not{b}$, in sequential increments of the parameter n of equation 1. The extinction index, n, of equation 1 is the independent variable of the parametric ROC plot for each member of the family, b_i (i = 1,2,3). Each curve begins with $n=0$ near the ROC point (1,0) and ends near (0,1) with $n>14$.

Neglecting the parameter, n, there is no significant difference in the ROC family of curves. The utility of the model is demonstrated by the low values of the points of minimum error rate: (0.12,0.12), (0.13,0.13), and (0.15,0.15), respectively for b_1, b_2, and b_3. But these points occur when the parameter, n, equals 4.25, 4.62, and 5.75, respectively, demonstrating that each fire state will have its own individual ROC.

The data points for b_1 at low n in figure 5A depart significantly from the ideal. This variance has roots in the physical observation process. The large miss error is because several fires burned that should not have been expected to burn; the low n indicates poor burning conditions, the state b_1 being fires that did not go out. By equation 1 these were fuel beds with light loading and/or high moisture content. It was noted during the experiment that a few of these fires could be sustained by two or three individual fuel sticks that may have had anomalously high heat of combustion (pitch and resins) or low moisture. In other fires with very light loading, the intersection of three or more sticks constituted a "jackpot" with significantly hotter fire behavior. The spatial distribution of these jackpots could not be controlled, even with extreme experimental precaution, to preclude some of the fires being sustained by jackpot-to-jackpot propagation, and which would have been predicted to go out if the fuel bed had been perfectly homogeneous. These inhomogeneities are insignificant in heavier loaded fuel beds, larger n, or do not affect our expectations for the hotter burning states. Thus there are two points to make:

1. Inhomogeneity is a physical variable that is not "recognized" in the fire model, is not incorporated in the likelihood ratios, nor in the ROC's, etc. It is, however, a parameter whose statistics could vary from one locality to another and so affect the prior odds on which the manager bases his decision.

2. These ROC curves indicate an ideal limit of performance; they represent the best that you can expect to do with the information observed and, in some cases, even that might be difficult to achieve.

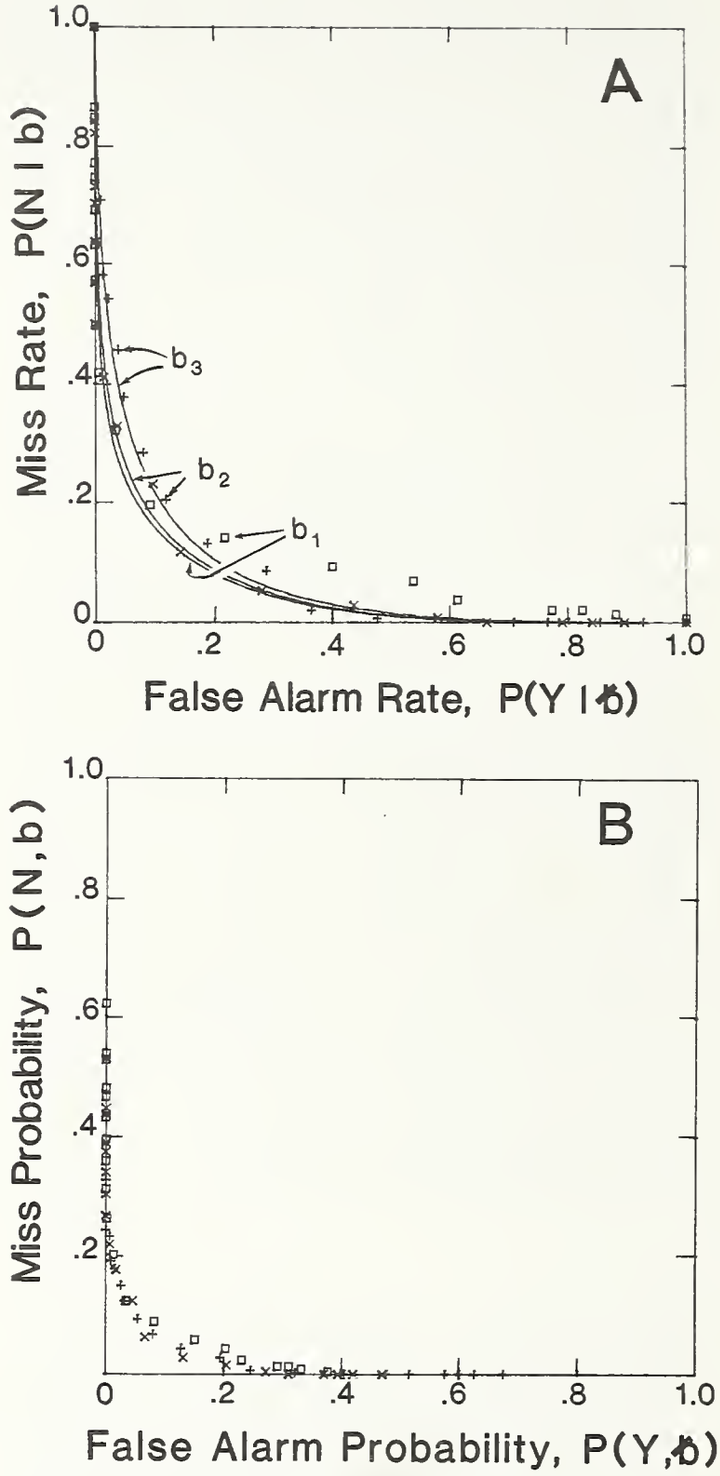


Figure 5—(A) ROC for the marginal fire states; (B) plot of posterior experimental errors where:

$P(Y,\not{b}) = P(Y|\not{b})\,P(\not{b})$ and

$P(N,b) = P(N|b)\,P(b)$.

In figure 5B the error rates are multiplied by their respective prior probabilities **of the experiment**, thus giving a plot of the expected errors for the experiment, namely, the joint probabilities. This plot is typical of what might be expected in a specific application, but of course it will vary by application because the prior probability distribution will vary substantially.

As we have noted, the distributions of marginal states, b, are bounded at the upper limit when 100 percent of the fireline is aflame. We have started a cursory examination of fire states defined in alternative terms of fire intensity without an upper bound. In particular, flame length is also a measure of intensity that shows promise of describing and discriminating between the hotter fire states. Preliminary analysis (of the 120+ "hot" fires $> b_3$) indicates a family of ROC curves that begin very close to those of figure 5A and then successively approach closer to the ROC origin as flame lengths lengthen.

CONCLUSIONS

The utility of a fire model in the decision process is greatly enhanced when a probable distribution of likely events is available to the decision maker. These distributions allow him to weigh the alternatives and risks involved, that is, to make good decisions. When a deterministic fire model gives a single value prediction, the fire manager is left wanting, with only his subjective experience as guide. How close to the true value is the prediction? What is the risk that it is wrong? Is the prediction appropriate to the local situation?

A fire model cannot be expected to respond to variations other than those observed and measured as inputs to the model. For a model to be widely useful, it should express the likelihood (as in equation 13 or in $P(n|b)$, etc.) that the currently measured physical conditions would be observed for the fixed fire state in question (or some equivalent expression). The model will, then, perform optimally, without built-in development biases and with a provision for differences between various localities (and times). A large portion of forestry literature is comprised of case studies, isolated anecdotal data, and reports of previously unobserved (rare) events. The task of compiling data bases for use of "expert systems" by decision makers must be done with such extreme care that the likelihood of any event, observation, or condition is not unreasonably overstated. Furthermore, isolated instances represent a single data point and not a distribution; hence, they are of little value to the person who must take risks when one does not know where in the distribution that data point might lie!

The next task is to develop a system for calculating ranges of fire behavior that fire managers will find useful and easily understood.

REFERENCES

Egan, James P. 1975. Signal detection theory and ROC analysis. New York: Academic Press. 277 p.

Hahn, G. J.; Shapiro, S. S. 1967. Statistical models in engineering. New York: Wiley and Sons. 355 p.

Larson, Harold J. 1969. Introduction to probability theory and statistical inference. New York: John Wiley and Sons. 387 p. (Ch. 9).

Rothermel, Richard C. 1972. A mathematical model for predicting fire spread in wildland fuels. Res. Pap. INT-115. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 40 p.

Savage, Leonard J. 1954. Foundations of statistics. New York: John Wiley and Sons. 294 p.

Slovic, Paul; Lichtenstein, Sarah. 1971. Comparison of Bayesian and regression approaches to the study of information processing and judgment. Organizational Behavior and Human Performance. 6: 649-744.

Wilson, Ralph A., Jr. 1985. Observations of extinction and marginal burning states in free burning porous fuel beds. Combustion Science and Technology. 44: 179-194.

Wilson, Ralph A., Jr. 1987. A theoretical basis for modeling probability distributions of fire behavior. Res. Pap. INT-382. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Research Station. 11 p.

A method is proposed for predicting a probabilistic distribution of fire behavior. A fire model gives conditional distributions of the physical fire site parameters one would observe for given fire states. The probabilistic prediction is provided by Bayes formula and knowledge of the prior distribution of fire states at specific sites. Thus, the fire model is independent of the site location. The techniques of plotting Receiver Operating Characteristics are demonstrated with examples to optimize and test the fire model's performance.

KEYWORDS: decision theory, marginal burning

INTERMOUNTAIN RESEARCH STATION

The Intermountain Research Station provides scientific knowledge and technology to improve management, protection, and use of the forests and rangelands of the Intermountain West. Research is designed to meet the needs of National Forest managers, Federal and State agencies, industry, academic institutions, public and private organizations, and individuals. Results of research are made available through publications, symposia, workshops, training sessions, and personal contacts.

The Intermountain Research Station territory includes Montana, Idaho, Utah, Nevada, and western Wyoming. Eighty-five percent of the lands in the Station area, about 231 million acres, are classified as forest or rangeland. They include grasslands, deserts, shrublands, alpine areas, and forests. They provide fiber for forest industries, minerals and fossil fuels for energy and industrial development, water for domestic and industrial consumption, forage for livestock and wildlife, and recreation opportunities for millions of visitors.

Several Station units conduct research in additional western States, or have missions that are national or international in scope.

Station laboratories are located in:

Boise, Idaho

Bozeman, Montana (in cooperation with Montana State University)

Logan, Utah (in cooperation with Utah State University)

Missoula, Montana (in cooperation with the University of Montana)

Moscow, Idaho (in cooperation with the University of Idaho)

Ogden, Utah

Provo, Utah (in cooperation with Brigham Young University)

Reno, Nevada (in cooperation with the University of Nevada)

USDA policy prohibits discrimination because of race, color, national origin, sex, age, religion, or handicapping condition. Any person who believes he or she has been discriminated against in any USDA-related activity should immediately contact the Secretary of Agriculture, Washington, DC 20250.